

Impact of nonintrusive load monitoring on CO₂ emissions in Malaysia

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ABSTRACT

Nonintrusive load monitoring (NILM) based energy efficiency can conserve electricity by creating awareness with the behaviour change and shrinking CO₂ emissions to the environment. However, the lack of effective models and strategies is problematic for policymakers to forecast quantitatively CO₂ emissions. This paper aims to study the impact of NILM on CO₂ emissions in Malaysia. Firstly, the predictive models were established based on Malaysia open data from 1996 to 2018. After that, scenario simulations were conducted to predict CO₂ emissions and NILM impact on environmental degradation in 2019-2030. The results revealed that a 12% reduction in electricity consumption due to NILM could contribute to a 10.2% shrinkage of the total CO₂ emissions. The result also statistically confirmed Malaysia to achieve a 45% reduction of CO₂ intensity in 2030. With NILM, the carbon reduction can be further enhanced to 60.2%. The outcomes provide valuable references and supporting evidence for policymakers in planning effective carbon emission control policies and energy efficiency measures. The work can be extended by developing a decision support system and user interfaces access via the cloud.

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1. INTRODUCTION

Sustainable development is a strategic approach to resolve the negative environmental consequences of economic growth and globalisation by finding possible solutions to remedy various problems caused by industrial and population growth [1]. As a developing nation, Malaysia gains rapid economic growth in industrialisation, urbanisation, and population growth since the 1980s. Undoubtedly, escalating demand for energy and electricity gives rise to energy demand and environmental degradation. Based on the energy commission (EC) of Malaysia [2], the total electricity consumption in 2018 marked 13,152 ktoe, or 4.33% higher than in 2017. The ever-growing demand for resources such as electricity escalating the global CO₂ emissions with environmental deterioration [3]. As a result, it is challenging to attain sustainable development of the country without strategic planning.

Governments and organisations have introduced numerous global and public policies targeting greenhouse gases (GHG) emissions mitigation. The United Nations Framework Convention on Climate Change Conference (UNFCCC) in Paris, or commonly known as COP21, mandated each country's responsibility to reduce CO₂ emission for heading towards a sustainable and low-carbon society [4]. To achieve the reduction target of CO₂ emissions, Malaysia has implemented many policies to mitigate the

environmental issue, particularly in terms of renewable energy and energy efficiencies (EE). In terms of residential and commercial buildings, the detailed information of electricity consumption using load monitoring, including the nonintrusive option (NILM) is a low-cost mechanism for analysing changes in single-source data from the metering and deducing individual electricity consumption of appliances [5]. Numerous use cases of NILM that can support EE include load demand forecasting, demand response and peak load shaving. As reported, a potential reduction of 12% of electricity consumption is achievable [6]. Ultimately, NILM opens up an opportunity to conserve electricity by creating awareness with the behaviour change and shrinking CO₂ emissions to the environment [7].

To assist the policymakers in tracking future trends of CO₂ emissions, the researchers carried out the forecasts from either regional or national level with different approaches [8], [9]. Many studies have revealed the relationship between several variables and energy consumption or energy-related CO₂ emissions. Some authors suggested independent variables such as residential household, industrial, manufacturing, commercial and transportation in analysing the relationship with energy consumption [10] or CO₂ emissions as responding variable [11], [12]. Apart from microscopic variables, the studies also conducted the relationship between the determinant variable with macroscopic variables such as gross domestic product GDP, population, urbanisation [10], and the single variable using GDP [13]. Several studies of scenario simulation method analyse the impacts of possible future CO₂ emissions by considering several alternative settings of predictors [14]-[17].

Previous literature provided good references to predicting CO₂ emissions and the issues of electricity conservation due to NILM [18]-[21]. However, a literature gap still exists regarding the study of NILM impact on CO₂ emissions, to the best of our knowledge. This paper aims to construct predictive models to evaluate the NILM impact on CO₂ emissions. Firstly, two predictive models are established with Malaysia open data from 1996 to 2018. Secondly, scenario simulations were adopted to predict CO₂ emissions in 2019-2030 with different scenarios to highlight the impact of NILM on CO₂ emissions reduction. As the largest source of CO₂ emissions, human activities with controlled energy consumption can directly affect emission mitigation [22]. Therefore, it is crucial to predict CO₂ emissions quantitatively for policymakers to monitor and manage the target policies and practices. Furthermore, the result also provides empirical evidence of the carbon reduction as Malaysia pledged in COP21.

2. RESEARCH METHOD

Figure 1 depicts the forecasting procedure in this paper. The study starts with developing predictive models of CO₂ emissions based on historical open data of the identified determinants derived from socioeconomic, demographic and technological innovations. Two regression models, namely multiple linear regression (MLR) and trend analysis (TA) models, are developed and eventually validated. Secondly, scenario simulation is conducted for CO₂ emissions forecasting and investigate the impact of the reduced electricity consumption due to NILM on environmental degradation in 2019-2030. MS Excel with the plugin package of data analysis is used to conduct modelling, testing and simulations in this study.

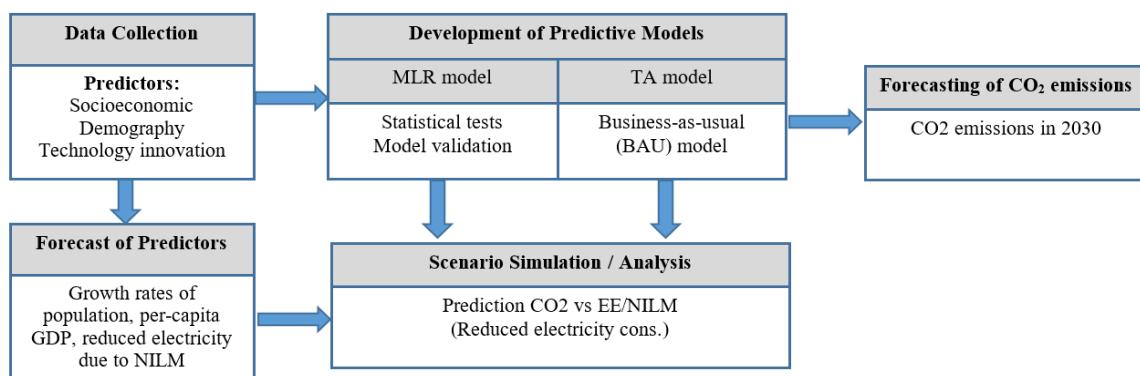


Figure 1. Flowchart of the forecasting process

2.1. Data collection

The study employs the historical annual time series data from World Bank Open Data's World Development Indicators (WDIs) [23] and Malaysia Energy Information Hub of Energy Commission of

Malaysia (MEIH) [24], from 1996 to 2018. The total CO₂ emissions (in thousand metric tons, kt) is chosen as the response variable. Several predictors are identified from socioeconomic, demography and technological innovation categories, namely per-capita gross domestic product GDP, per-capita electricity consumption (in kWh), R&D expenditure (in % of GDP), FDI net inflows (in Billion US\$), generation (RE) (in % of total) and generation (fossil) (in % of total). The dataset is tested for normality before selecting significant predictors by the stepwise regression search method for modelling.

2.2. Predictive models

The MLR model is essentially a statistical regression technique that uses a group of predictors to predict the outcome of a response variable Y . It essentially gives more explanatory power to the regression model by including additional predictor variables [14]. The model is generally written as (1) as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \dots + \beta_k X_k + \varepsilon \quad (1)$$

where k is the number of independent variables, β_0 is the intercept term, β_1, \dots, β_k are regression coefficients, and ε is the random error term of the model. The derived MLR model is statistically tested and adopted for scenario simulation to forecast CO₂ emissions in 2019-2030.

On the other hand, TA model is used to predict future CO₂ emissions owing to its simplicity. The projections are based on what has happened in the past explains what will happen in the future [25], [26]. For forecasting of the CO₂ emissions, the trends during 1996-2018 are first identified. According to the observed trend, the TA model is expressed as a regression function of the year as (2) to predict CO₂ emissions.

$$Y = f(Year, Year^2) \quad (2)$$

2.3. Model validity

The regression models are rooted strongly in the field of statistical learning. Therefore, the model's goodness-of-fit tests are carried out to inspect the validity of the derived models, namely R-squared, T-test and F-test. Mean absolute percentage error (MAPE) is calculated as the deviation between the model's predicted values and actual values in the data population. It is calculated using (3) as a dimensionless index. The lower the value of MAPE, the better its performance [27].

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{A_t - P_t}{A_t} \right| \times 100\% \quad (3)$$

where A_t is representing the actual value, n represents the number of observations, and P_t denotes the predicted value.

2.4. Prediction of CO₂ emissions in 2019-2030

In order to forecast CO₂ emissions and evaluate the NILM impact on CO₂ emissions, both TA and MLR models are adopted in scenario simulations of the environmental degradation (2019-2030) in Malaysia. The MLR model predicts CO₂ emissions, apart from evaluating CO₂ emissions under the influence of electricity conservation due to NILM. On the other hand, the TA model predicts future CO₂ emissions based on the historical trends under the compound effect of different factors. It is a so-called business-as-usual (BAU) model without considering the influence of NILM on CO₂ emissions forecasting. By comparing the results from scenario simulations, the future CO₂ emissions and the impact of NILM-based measure on environmental degradation in Malaysia are determined. Compared to [14] for technological innovation impact, this study emphasised the evaluation of the NILM impact on environmental degradation.

3. RESULTS AND DISCUSSION

3.1. Modeling results and validity

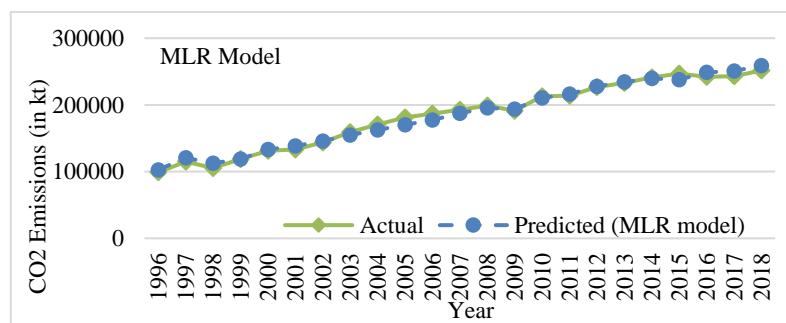
Based on the regression results of the MLR model are listed in Table 1 (a), the R-squared of 0.978 indicates that the selected predictors can explain 97.8% of the variation in CO₂ emissions. The coefficients of ln GDP and ln kWh have positive correlations with CO₂ emissions. Based on p-values of 0.006779 and 5.15E-09 (<0.05), both coefficients have passed the T-test for the significance individually to the model. With the regression coefficients, the relationship between the predictors and CO₂ emissions (in kt) is translated into MLR (4). ln kWh parameter is identified as the best predictor in the MLR model as it is the most effective in predicting CO₂ emissions in Malaysia.

$$CO_2(kt) = -1385960 + 27740.41 \ln GDP + 162742.2 \ln kWh \quad (4)$$

The F-test of overall significance with a *Signif-F* value of 9.69E-18 (<0.05) in Table 1 (b) has confirmed the model's goodness-of-fit. The comparison of actual and predicted CO₂ emissions values between 1996 and 2018 is depicted in Figure 2. The predicted CO₂ emissions are very close to the actual ones, with a low MAPE value of 0.04%.

Table 1. Regression estimation results

(a) Regression statistic		(b) Significance F						
Regression Statistics		MLR Model	Coefficients	Std.Error	t Stat	P-value	Signif-F	MAPE
Multiple R	0.99001	(Constant)	-1385960	70279.94	-19.7206	1.41E-14	9.69E-18	0.04%
R Square	0.98011	ln GDP	27740.4	9188.484	3.019041	0.006779		
Adjusted R Square	0.97812	ln kWh	162742.2	16754.34	9.713436	5.15E-09		
Standard Error	7401.66							
Observations	23							

Figure 2. Comparison of actual and predicted CO₂ by MLR model

On the other hand, the regression results of the TA model are listed in Table 2 (a). The R-squared of 0.985 indicates that the predictors can explain 98.5% of the variation in CO₂ emissions. The coefficients have p-values of 0.000555 and 0.000631 (<0.05), respectively. Hence, the terms of *year* and *year*² have passed the T-test for the significance individually to the model. Therefore, the TA model equation is written as a polynomial regression shown in (5).

$$CO_2(kt) = 83449 + 10497 Year - 133.93 Year^2 \quad (5)$$

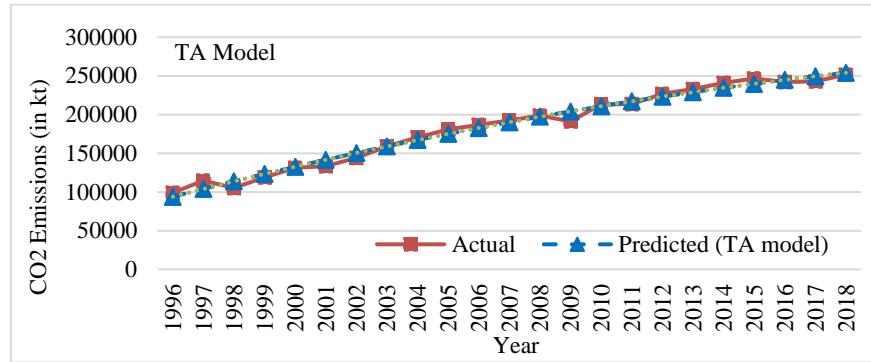
The F-test of overall significance with a *Signif-F* value of 3.08E-19 in Table 2 (b) has confirmed the model's goodness-of-fit. The comparison of actual and predicted CO₂ emissions values between 1996 and 2018 is depicted in Figure 3. The predicted CO₂ emissions are very close to the actual ones, with a low MAPE value of 0.05%. Chang *et al.* [28] suggested that the model performance can be classified according to MAPE metric. The model is excellent if MAPE is less than 10%, while MAPE between 10-20% is considered acceptable. Hence, the results have confirmed the creditability and well-fitted the models to forecast the CO₂ emissions in Malaysia.

Table 2. Regression estimation results

(a) Regression statistic		(b) Significance F						
Regression Statistics		TA Model	Coefficients	Std.Error	t Stat	P-value	Signif-F	MAPE
Multiple R	0.992931	Intercept	-5.5E+08	1.33E+08	-4.15467	0.00049	3.08E-19	0.05%
R Square	0.985913	Year	544869.8	132854.7	4.101247	0.000555		
Adjusted R Square	0.984504	Year ²	-133.928	33.09779	-4.04643	0.000631		
Standard Error	6229.07							
Observations	23							

3.2. Scenario simulations

This section studied the impact of electricity conservation due to NILM on environmental degradation. The scenario simulations are conducted to reveal the insights of NILM impact. The scenario simulations are conducted by setting 5 (five) scenarios to analyse CO₂ emissions from 2019 to 2030.

Figure 3. Comparison of actual and predicted CO₂ by MLR model

3.2.1. The growth rate of predictors

To predict Malaysia's CO₂ emissions in 2019-2030, the values of predictor variables in (4), i.e. GDP and electricity consumption, need to be known such that CO₂ emissions can be forecasted. The growth rates of the variables set based on the relevant research institution or policies.

- Population; Malaysia's population growth rate is ranging from 1.3-1.4% from 2012 to 2018. The Malaysia population forecast data from 2019-2030 is based on World Bank Data with the exponential growth formula assumes a constant growth rate between two points in time.
- GDP per capita; the average growth rate of GDP based on the historical data in 2011-2018 is 5.17%. Due to the pandemic of covid-19, Malaysia marked GDP growth of -6% but forecasted to recover after that. Malaysia GDP has an annual growth rate of 4.8% in 2019-2025 as forecasted by the International Monetary Fund (IMF) report [29]. In this study, we extend the same rate from 2026 to 2030 for scenario simulations.
- Electricity consumption; the historical data was extracted from the Malaysia Energy Information Hub (MEIH) of Malaysia's Energy Commission. According to World Energy Markets Observatory (WEMO) 2017 report, electricity consumption is projected to increase by 4.8% annually right up to 2030 [30]. Scenario 1 with an annual growth rate of 4.8% of electricity consumption as the baseline for forecasting between 2019 and 2030. Scenarios 2-5 set the electricity consumption with the baseline and different reduction percentages (2~12%) due to the NILM effect.

3.2.2. Predicted CO₂ emissions for 2019-2030

There are five scenario settings in the simulation set, as listed in Table 3. Designated as the baseline scenario, Scenario 1 employs the TA model to forecast CO₂ emissions in 2019-2030 based on historical data without considering NILM impact. Scenarios 2-5 highlight the NILM-based EE with different reduction percentage in electricity consumption, on top of the annual base rate of 4.8% increment. Other variables set by the forecast data 2019-2030 as described. The five scenarios are simulated to forecast Malaysia's CO₂ emission values in 2019-2030, as depicted in Figure 4.

Table 3. Scenarios setting of Malaysia

Scenario	Population	GDP	The setting of growth rate	
				Electricity consumption
1.		The estimated CO ₂ emissions by TA model as BAU scenario.		
2.	Use predicted World Bank Data.	Use a 4.8% growth rate.	Baseline (+4.8%) with a reduction of 2% of electricity consumption	
3.	(specific exponential growth rate formula applied)	(Predicted rate by IMF and extension to 2030)	Baseline with a reduction of 5%	
4.			Baseline with a reduction of 8%	
5.			Baseline with a reduction of 12%	

* Scenario 1 adopts the TA model, while scenarios 2-5 adopt the MLR model to forecast CO₂ emissions for 2019-2030.

In this case, the TA model used in Scenario 1 serves as business-as-usual (BAU) by considering the compound effect of various predictor variables without any additional electricity conservation due to NILM. On the other hand, scenarios 2-5 forecast the CO₂ emissions values by considering the impact of NILM. Therefore, the significance of the NILM on CO₂ emissions in Malaysia can be highlighted. Compared with BAU (Scenario 1), the reduction of electricity consumption due to NILM-based EE (Scenario 2-5) has reduced the CO₂ emissions from 351,739kt to 315,862kt. Although a 10.2% shrinkage of CO₂ emissions, the trend shows the peaking of CO₂ emissions is still far to be achieved by 2030.

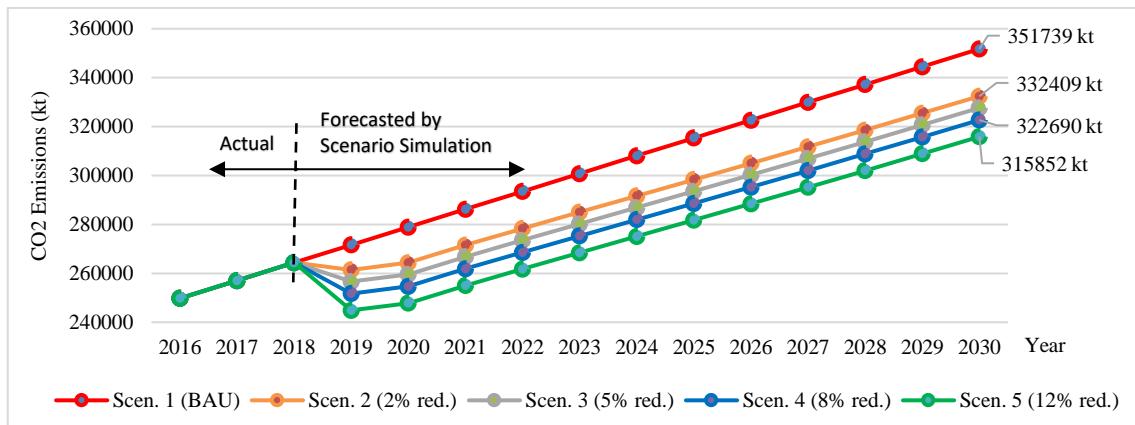
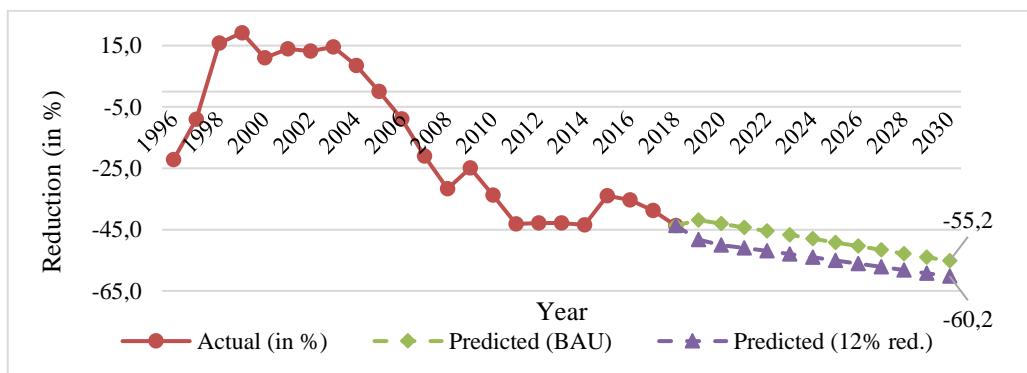


Figure 4. The results of scenario simulations in Malaysia

3.3. Forecasting of carbon intensity forecasting of Malaysia by 2030

Malaysia has pledged to Nationally Determined Contribution (NDC) of UNFCCC for 45% reduction of GHG emissions, i.e. per-GDP emission intensity by 2030 (relative to 2005) [31]. More specifically, the pledge consists of a 35% reduction of unconditional basis and an additional 10% reduction on a conditional basis, i.e. upon receiving support from developed countries, including climate finance, technology transfer, and capacity building. Malaysia has implemented various policies and efforts to fulfil its commitment to the reduction of environmental degradation. Based on the performance of CO₂ intensity per GDP shown in Figure 5, the projection with scenario 1 has shown a reduction of 55.3% (relative to 2005) in 2030. Furthermore, the CO₂ emission intensity in 2030 can be further improved by an additional 5% due to the adoption of NILM-based measure. Therefore, Malaysia should employ various policies and mechanisms, such as NILM and its use cases, to substantially reduce electricity consumption and CO₂ emissions for financial saving and environmental improvement.

Figure 5. Percentage change of CO₂ emission intensity from 1996-2030 (in relative to 2005 level)

4. CONCLUSION

As committed to UNFCCC of environmental improvement in 2030, it is crucial to translate the goal into effective planning with analytical and monitoring tools. The scenario simulation result revealed that a 12% reduction in electricity consumption due to the NILM-based EE had caused a 10.2% shrinkage of the total CO₂ emissions. Meanwhile, the result also affirmed the possibility of achieving Malaysia's commitment to UNFCCC to lower CO₂ intensity per unit GDP by 45% by 2030. More specifically, the reduction of 57.43%-61.40% due to the impact of NILM. Nevertheless, the trend shows that Malaysia's total CO₂ emissions will continue to increase until 2030 without reaching the peak. Hence, Malaysia needs good policies to promote green technology and renewable energy and encourage Malaysians to be more aware of environmental sustainability and use energy efficiently. Apart from that, the generation of renewable energy and R&D expenditure of Malaysia is still far limited to bring any significant effect to reduce CO₂ emissions of the country. The outcomes provide valuable references and supporting evidence for policymakers in

planning effective carbon emission control policies and action plans. The work can be extended by developing a decision support system and user interface via the cloud.

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REFERENCES

- [1] J. Mensah, "Sustainable development: Meaning, history, principles, pillars, and implications for human action: Literature review," *Cogent Soc. Sci.*, vol. 5, no. 1, Jan. 2019, doi: 10.1080/23311886.2019.1653531.
- [2] *Malaysia energy statistics*, Suruhanjaya Tenaga (Energy Comm), 2019.
- [3] United Nation Development Programme (UNDP), *Achieving industrial energy efficiency in Malaysia*, Kuala Lumpur, Malaysia, 2006.
- [4] "Adoption of the paris agreement," *Conference of the Parties, Twenty-first session*, Paris, 30 November to 11 December 2015.
- [5] M. Gaur and A. Majumdar, "Disaggregating transform learning for non-intrusive load monitoring," *IEEE Access*, vol. 6, pp. 46256-46265, 2018, doi: 10.1109/ACCESS.2018.2850707.
- [6] K. Carrie Armel, A. Gupta, G. Shrimali, and A. Albert, "Is disaggregation the holy grail of energy efficiency? The case of electricity," *Energy Policy*, vol. 52, pp. 213-234, 2013, doi: 10.1016/j.enpol.2012.08.062.
- [7] L. Pereira and N. Nunes, "Understanding the practical issues of deploying energy monitoring and eco-feedback technology in the wild: Lesson learned from three long-term deployments," *Energy Reports*, vol. 6, pp. 94-106, Nov. 2020, doi: 10.1016/j.egyr.2019.11.025.
- [8] Y. Yang, J. Zhang, and C. Wang. (2013). Is China on track to comply with its 2020 Copenhagen carbon intensity commitment? [Online]. Available: <https://escholarship.org/uc/item/1r5251g8>.
- [9] W. Wei, *et al.*, "Carbon emissions of urban power grid in Jing-Jin-Ji region: Characteristics and influential factors," *J. Clean. Prod.*, vol. 168, pp. 428-440, 2017, doi: 10.1016/j.jclepro.2017.09.015.
- [10] W. Zhou, B. Zhu, D. Chen, C. Griffy-Brown, Y. Ma, and W. Fei, "Energy consumption patterns in the process of China's urbanization," *Popul. Environ.*, vol. 33, no. 2-3, pp. 202-220, 2012, doi: 10.1007/s11111-011-0133-5.
- [11] M. Shahbaz, N. Loganathan, A. T. Muzaffar, K. Ahmed, and M. Ali Jabran, "How urbanization affects CO₂ emissions in Malaysia? the application of STIRPAT model," *Renewable and Sustainable Energy Reviews*, vol. 57, pp. 83-93, 2016, doi: 10.1016/j.rser.2015.12.096.
- [12] K. J. Yii and C. Geetha, "The nexus between technology innovation and CO₂ emissions in Malaysia: Evidence from granger causality test," *Energy Procedia*, vol. 105, pp. 3118-3124, 2017, doi: 10.1016/j.egypro.2017.03.654.
- [13] Z.-X. Wang, "A predictive analysis of clean energy consumption, economic growth and environmental regulation in china using an optimized grey dynamic model," *Comput. Econ.*, vol. 46, no. 3, pp. 437-453, Oct. 2015, doi: 10.1007/s10614-015-9488-5.
- [14] Y. Yu and Y. Du, "Impact of technological innovation on CO₂ emissions and emissions trend prediction on 'New Normal' economy in China," *Atmos. Pollut. Res.*, vol. 10, no. 1, pp. 152-161, 2019, doi: 10.1016/j.apr.2018.07.005.
- [15] S. M. Hosseini, A. Saifoddin, R. Shirmohammadi, and A. Aslani, "Forecasting of CO₂ emissions in Iran based on time series and regression analysis," *Energy Reports*, vol. 5, pp. 619-631, Nov. 2019, doi: 10.1016/j.egyr.2019.05.004.
- [16] S. Y. Balaman, "Uncertainty issues in biomass-based production chains," in *Decision-Making for Biomass-Based Production Chains*, 2019, pp. 113-142, doi: 10.1016/B978-0-12-814278-3.00005-4.
- [17] J. Seo, H. Kim, and S. Park, "Estimation of CO₂ emissions from heavy-duty vehicles in Korea and potential for reduction based on scenario analysis," *Sci. Total Environ.*, vol. 636, pp. 1192-1201, Sep. 2018, doi: 10.1016/j.scitotenv.2018.04.269.
- [18] F. D. Garcia, W. A. Souza, I. S. Diniz, and F. P. Marafão, "NILM-based approach for energy efficiency assessment of household appliances," *Energy Informatics*, vol. 3, no. 10, 2020, doi: 10.1186/s42162-020-00131-7.
- [19] A. Ruano, A. Hernandez, J. Ureña, M. Ruano, and J. Garcia, "NILM techniques for intelligent home energy management and ambient assisted living: A review," *Energies*, vol. 12, no. 11, p. 2203, Jun. 2019, doi: 10.3390/en12112203.
- [20] S. S. Hosseini, K. Agbossou, S. Kelouwani, and A. Cardenas, "Non-intrusive load monitoring through home energy management systems: A comprehensive review," *Renewable and Sustainable Energy Reviews*, vol. 79, pp. 1266-1274, 2017, doi: 10.1016/j.rser.2017.05.096.
- [21] R. Gopinath, M. Kumar, C. Prakash Chandra Joshua, and K. Srinivas, "Energy management using non-intrusive load monitoring techniques-State-of-the-art and future research directions," *Sustainable Cities and Society*, vol. 62, p. 102411, 2020, doi: 10.1016/j.scs.2020.102411.
- [22] J. C. Yeh and C. H. Liao, "Impact of population and economic growth on carbon emissions in Taiwan using an analytic tool STIRPAT," *Sustain. Environ. Res.*, vol. 27, no. 1, pp. 41-48, Jan. 2017.
- [23] "World Development Indicators World Bank DataBank." <https://databank.worldbank.org/source/world-development-indicators>. accessed Mar. 10, 2021).
- [24] "Malaysia Energy Commission (EC). Malaysia Energy Information Hub-Statistics."

<https://meih.st.gov.my/statistics> (accessed Mar. 10, 2021).

[25] T. R. Anderson, E. Hawkins, and P. D. Jones, “CO₂, the greenhouse effect and global warming: from the pioneering work of Arrhenius and Callendar to today’s Earth System Models,” *Endeavour*, vol. 40, no. 3, pp. 178-187, Sep. 2016, doi: 10.1016/j.endeavour.2016.07.002.

[26] H. Wachtmeister, P. Henke, and M. Höök, “Oil projections in retrospect: Revisions, accuracy and current uncertainty,” *Appl. Energy*, vol. 220, pp. 138-153, Jun. 2018, doi: 10.1016/j.apenergy.2018.03.013.

[27] O. O. Olatunji, S. Akinlabi, N. Madushele, P. A. Adedeji, and I. Felix, “Multilayer perceptron artificial neural network for the prediction of heating value of municipal solid waste,” *AIMS Energy*, vol. 7, no. 6, pp. 944-956, 2019, doi: 10.3934/energy.2019.6.944.

[28] Y. F. Chang, C. J. Lin, J. M. Chyan, I. M. Chen, and J. E. Chang, “Multiple regression models for the lower heating value of municipal solid waste in Taiwan,” *J. Environ. Manage.*, vol. 85, no. 4, pp. 891-899, 2007, doi: 10.1016/j.jenvman.2006.10.025.

[29] I. M. F. Asia and P. Dept, “Malaysia: 2021 article IV consultation—press release; staff report; and statement by the Executive Director for Malaysia,” *IMF Staff Ctry. Reports*, vol. 2021, no. 053, p. A002.

[30] “World energy markets observatory (WEMO). A strategic overview of the global energy markets. 2017,” 2017.

[31] MESTECC Malaysia, *Environment and climate change Malaysia third national communication and second biennial update report to the UNFCCC 2018*, Kuala Lumpur, Malaysia, 2018.

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